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A Study On Generation Of An Example Shape Using Less Number Of Land Marking Points In Active Shape Model

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Abstract

The Active Shape Model (ASM) is one of the most popular local texture models for face alignment. It applies in many fields such as locating facial features in the image to classify or make measurements, face synthesis etc. This paper has proposed some improvements on the classical ASM to increase the performance of the model in the face alignment application. Here, Only 15 'land marking' points are used as a parameter to generate an example shape . In this paper it has been shown several practical examples where we have manually built such example shapes and used them for further processing.

Keywords*: ASM, Face alignment, face synthesis, facial landmark.*

1. Introduction

Images usually contain complex objects, which will alter in appearance significantly from one image to another [1]. It can be a very difficult task to measure or detect the presence of those objects in any particular image. The shape model represents the expected shape and local grey-level structure of a target object in an image. Model-based methods make use of a prior model of what is expected in the image, and typically attempt to find the best match of the model to the data in a new image. Having matched the model, one can then make measurements or tests whether the target is actually present.

A model is trained from a set of images annotated by a human expert. By analysing the variations in shape and appearance over the training set, a model is built which can mimic this variation. To interpret a new image we must find the parameters which best match a model instance to the image. Having fit the Model to the image, the parameters or the model point positions can be used to classify or make measurements, or as an input to further processing.ASM is a statistical approach, in which a model is first built from analyzing the appearance of a set of labelled examples. It is an iterative method of matching model to image. A new image can be interpreted by finding the best valid match of the model to the image data.

The general idea of ASM is (1) try to locate each landmark independently and then
(2) correct the locations if necessary by looking at how the landmarks are located with respect to each other.

Advantages of ASM:

Fast, simple, accurate. Efficient to extend to 3D.It is widely applicable. The same algorithm can be applied to many different problems. Expert knowledge can be captured in the system in the annotation of the training examples. The system need make few prior assumptions about the nature of the objects being modelled, other than what it learns from the training set [1].

Disadvantages of ASM:

They are not necessarily appropriate for Objects with widely varying shapes (e.g. amorphous things, trees, long wiggly worms etc).Problems involving counting large numbers of small things. ASM is not appropriate for Problems in which position/size/orientation of targets is not known approximately. [1].

In this paper, we have proposed a technique to build the example shapes. We have contributed some improvement on the classical ASM to increase the performance of the model in the application: face alignment. We have used less no of landmark points (15 points) to generate the example shapes in ASM. Results on different neutral frontal images (“Fig.4”) are discussed .The remainder of the paper is organized as follows.

Database description is presented in Section 2. Section 3 covers the related work. Section 4 outlines the methodology of the present work through various subsections. Description of future plan of our work along with conclusion is presented in Section 5.

2. Database

The Pictures of different persons (Fig.4) are used to test the method developed for creation of facial example shape model. For our purpose we have used only the Neutral (full illumination frontal) image. The resolutions of these facial images are 1936 X 1288.

3. Review Work

T.Cootes [1] proposed the classical ASM method where he used 133 landmarking points to generate the example shapes. He used PCA to reduce the dimension. The model had 36 parameter. J.Shi, A.Samal, D.Marx,[2] proposed a technique which evaluates how biologically meaningful landmarks and their geometry extracted from face images can be used for face recognition. They used only 29 landmark points for face recognition.Hamdi Dibeklioglu et al. [3] proposed a technique for Automatic facial-landmark localization. .They used 22 landmarks. Their method achieved 99.33% accuracy on the Bosphorus database and 97.62% accuracy on the BioID database on the average. Stefano Arca et al.[4] proposed a feature-based approach. They presented completely automatic face recognition system .The method works on colour images: after having localized the face and the facial features, it determines 24 facial fiducial points. Yun et al.[5] proposed an automatic and robust method of facial fiducial point’s detection for facial expressions analysis in video sequences using scale invariant feature based Adaboost classifiers. The results showed that their method achieved a good Performance of 90.69 % average recognition rate. They choose 26 fiducial points on the face region from training samples to build the fiducial point detectors with Adaboost classifiers.Tie Yun et al.[6] proposed an automatic fiducial points tracking method from various facial expressions using multiple Differential Evolution Markov Chain (DE-MC) particle filters with kernel correlation techniques.Their method achieved **92%** accuracy of the tracking performance over the RML(Ryerson Multimedia Research Laboratory) Emotion Database and Mind Reading DVD (Digital Versatile Disc) database.

It can be inferred that any face image can be aligned easily using less no of landmark points. No need to localize too many landmark points to generate the example shapes because It will be very difficult task to store all those points manually if there is large number of landmark points.

4. Methodology

“Fig.1” represents the 4 phases of our proposed method to generate the example shapes and the mean of example shapes. These 4 phases are discussed later in the paper.

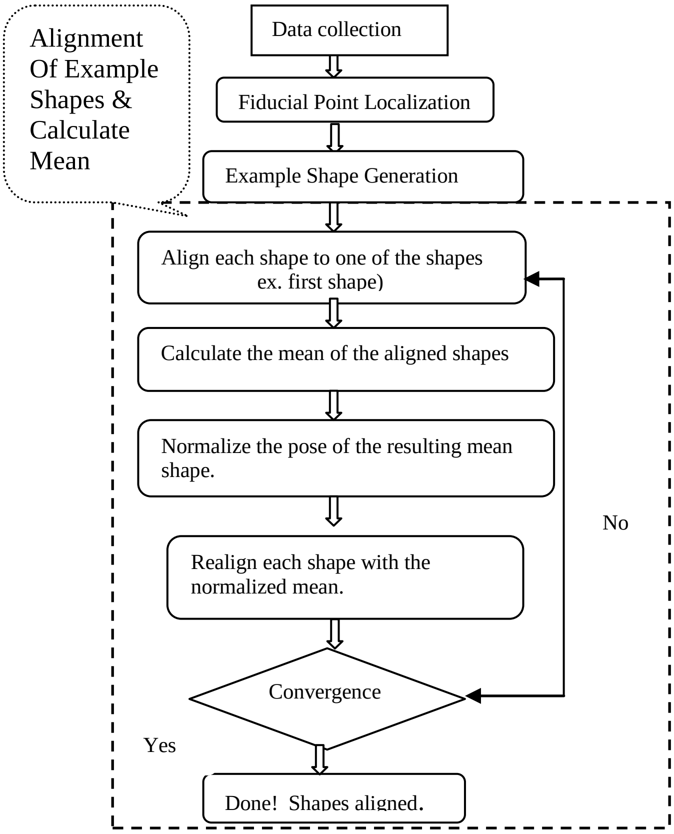

Figure 1. Phases of Example Shape Generation Phases

Data Collection

The Data collection is the process of preparing and gathering data.In this phase we have colllected the neutral images of 13 persons ”Fig. 5” for creation of facial example shape model.

Fiducial Point Localization

ASM need a user to be able to mark ‘landmark’ points on each of a set of training images in such a way that each landmark represents an identifiable point present on every example image. There are some basic principles that suggest where to choose the landmark points of a shape[1].

In this phase, we have taken neutral facial image as input which gave output, images having annotated with landmarks. Here, in “Fig. 2” we have manually place 15 ‘landmark’ points over the frontal human faces. The position of those points in anyhuman face are as follows:

01. Right eyebrow’s right end point.
02. Right eyebrow’s left end point.
03. Left eyebrow’s right end point.
04. Left eyebrow’s left end point.
05. Left eye’s left corner.
06. Left eye’s right corner.
07. Right eye’s left corner.
08. Right eye’s right corner.
09. Right nose point.
10. Left nose point.
11. Nose tip point.
12. Left lip corner.
13. Upper middle point of the lip.
14. Right lip corner.
15. Lower middle point of the lip.

The Coordinate values of those 15 landmark points of only 4 persons (out of 13 persons) are shown in the following tables from“Table.1-Table.4”.

Figure 2. Annotated Facial Landmark Points

Table 1. Person1 Coordinate Values

Point No	Coordinate Value
1	1076,581
2	943,576
3	847,571
4	718,576
5	748,618
6	836,635
7	955,639
8	1046,627
9	919,772
10	859,771
11	888,746
12	809,868
13	891,839
14	972,869
15	891,888

Table 2. Person2 Coordinate Values

Point No	Coordinate Value
1	1174,571
2	1002,592
3	949,594
4	780,589
5	828,634
6	914,645
7	1048,634
8	1134,621
9	1013,759
10	951,760
11	982,728
12	893,862
13	987,829
14	1085,853
15	987,875

Table 3. Person3 Coordinate Values

Point No	Coordinate value
1	1170,602
2	990,577
3	901,570
4	729,567
5	774,618
6	874,631
7	1009,638
8	1110,634
9	975,788
10	899,786
11	940,756
12	855,879
13	938,847
14	1031,881
15	939,927

Table 4. Person4 Coordinate Values

Point No	Coordinate value
1	1181,614
2	1004,602
3	930,605
4	756,614
5	809,654
6	898,660
7	1035,657
8	1130,651
9	994,782
10	930,783
11	965,753
12	878,889
13	966,846
14	1059,880
15	971,906

Example Shape Generation

The example shape represents the expected shape and local grey-level structure of a target object in an image. Example shapes are generated from the annotated visual images. To form the boundaries in the image we must record the connectivity between the landmark points, connectivity allows determining the direction of the boundary at a given point i.e. how the landmarks are joined with each other.

Suppose the landmarks along a curve are labeled $\{(x_1, y_1), (x_2, y_2), \ldots,(x_n, y_n)\}$.For a 2-D single image example we can represent the n landmark points,$\{(x_i, y_i)\}$ [Where i=1 to n], as the 2n element vector, **X**. Where $\mathbf{X} = (x_1. \, . \, . \, x_n, y_1 \, . \, . \, . \, y_n)^T$ …….(1)

If we have s training examples, we generate s such vector $\mathbf{X}_j$ [where i =1to s]. To form the required example shape we have to join those 15 Landmark points in “Fig. 3”. The way we have connected those points with each other is as follows.

1. Join between Right eyebrow’s right and left end point.
2. Join between left eyebrow’s right and left end point.
3. Join left eyebrow’s left end point and left eye’s left corner.
4. Join Left eye’s left corner and left eye’s right corner.
5. Join Right eye’s left corner and Right eye’s right corner.
6. Join Right eye’s right corner and Right eyebrow’s right end point.
7. Join Left eye’s right corner and Left nose point.
8. Join Left nose point and Nose tip point.
9. Join Right nose point and Nose tip point.
10. Join Right nose point and Right eye’s left corner.
11. Join Left eye’s left corner and Left lip corner.
12. Join Right eye’s right corner and Right lip corner.
13. Join Left corner and Upper middle point of the lip.
14. Join Upper middle point and Right corner of the lip.
15. Join Right lip corner and Lower middle point of lip.
16. Join Left lip corner and Lower middle point of the lip.

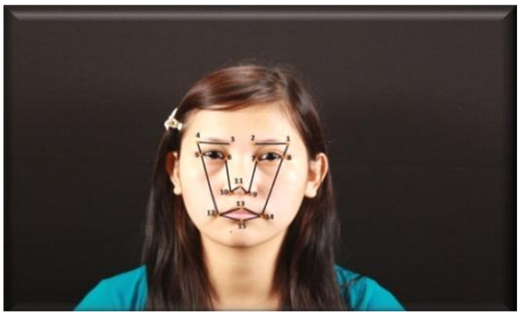

Figure 3. Example Shape Generation.

Figure 4. Neutral Expression of 13 Different Human Faces

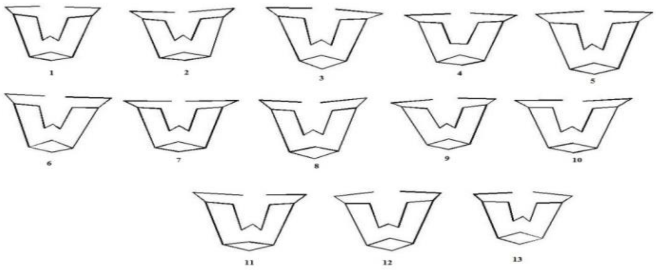

Figure 5. Example Shapes Generated From 13 Training Examples

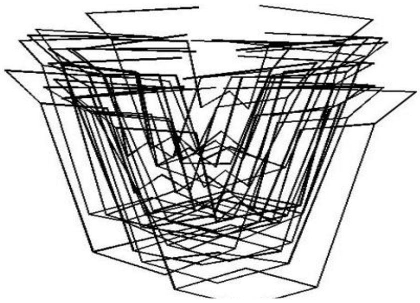

Figure 6. Example Shapes Aligned Into Same Coordinate Frame

In “Fig. 4” we have taken 13 training examples of human faces to generate the example shapes. Manually we have taken 15 land marking points position (as shown in “Fig. 2”) from each of these human faces to generate the subsequent example shapes. We have manually stored the coordinate values of those landmarking points as a feature vector to generate the following example shapes in “Fig. 5 ”.With the help of Matlab we have generated these following shapes. These example shapes are less complicated then the classical ASM had.

Alignment Of Example Shapes & Calculate Mean

Before performing the statistical analysis on these vectors [X_i]/example shapes/training shapes, it is important that the shapes represented are in the same co-ordinate frame. The approach for aligning a set of training shapes into a common Co-ordinate frame is to translate, rotate and scale each shape so that the sum of square distances of each shape to the mean is minimized[1]. Face alignments objective “in Fig. 6” is to localize the feature points on face images such as the shape points of eye, nose, mouth and face [7].In “Fig. 6” we have aligned 13 example shapes from “Fig. 5”.

Here Normalization is carried out in order to force the process to converge, otherwise the mean shape may translate or expand (or shrink) indefinitely. Convergence is established if the shapes are not changing more than a pre-defined threshold[1].

Mean of the data is calculated by using the following eqn.

$$\bar{x} = \frac{1}{s}\sum_{i=1}^{s} x_i \quad\text{..................}(2)$$

Here, xi= 2n element vector. S= total no of shapes [1]

The mean face in ”Fig. 7” is initially placed in any given input image to search the presence of any face object in that input image.

Mean Face Coordinate Value Calculation

The experiment generated the coordinate values of the mean face from 13 example shapes using the eqn… "(2)".The coordinate values(land marking points) of the mean shapes is as follows: SYSTEM OVERVIEW

Mean of the point positions for the point 1 is as follows [{1/13*(1076+1174+1170+1181+1236+1143+1183+1107+1173+1199+1194+1192+1180)},{1/13*(581+571+602+614+662+582+652+613+650+579+655+572+541)}] = (1169, 605)

Mean of the point positions for the point 2 is as follows [{1/13*(943+1002+990+1004+1055+970+985+932+1028+1014+1042+1039+1032)},{1/13*(576+592+577+602+655+575+656+640+645+595+656+563+517)}]= (1002, 603)

Mean of the point positions for the point 3 is as follows [{1/13*(847+949+901+930+974+891+931+860+933+938+953+937+952)},{1/13*(571+594+570+605+655+569+656+ 638+653+589+658+566+520)}] = (922, 603)

Mean of the point positions for the point 4 is as follows [{1/13*(718+780+729+756+793+740+750+700+774+756+763+788+805),{1/13*(576+589+567+614+672+557+654+626+673+590+641+592+530)}] = (757, 606)

Mean of the point positions for the point 5 is as follows [{1/13*(748+828+774+809+845+775+804+746+817+809+813+829+839),{1/13*(618+634+618+654+723+616+694+682+697+633+699+634+575)}] = (802, 652)

Mean of the point positions for the point 6 is as follows [{1/13*(836+914+874+898+949+870+891+833+913+901+916+923+938),{1/13*(635+645+631+660+731+629+700+690+707+633+712+635+577)}]=(896,660)

Mean of the point positions for the point 7 is as follows [{1/13*(955+1048+1009+1035+1085+995+1027+976+1048+1053+1055+1064+1045),{1/13*(639+634+638+657+726+638+702+688+702+638+714+629+583)}]= (1030, 660)

Mean of the point positions for the point 8 is as follows [{1/13*(1046+1134+1110+1130+1182+1094+1123+1068+1137+1146+1147+1163+1141),{1/13*(627+621+634+651+716+ 639+692+672+685+629+706+617+580)}] = (1124, 651)

Mean of the point positions for the point 9 is as follows [{1/13*(919+1013+975+994+1048+949+996+941+1017+1010+1023+1031+1018),{1/13*(772+759+788+782+881+762+831+828+820+776+863+774+690)}]=(994,79)

Mean of the point positions for the point 10 is as follows [{1/13*(859+951+899+930+976+890+923+869+960+932+948+958+956),{1/13*(771+760+786+783+880+758+831+832+822+776+863+777+688)}]=(927,794)

Mean of the point positions for the point 11 is as follows [{1/13*(888+982+940+965+1007+923+960+905+988+975+992+994+993),{1/13*(746+728+756+753+847+734+800+801+794+744+828+754+661)}] = (962, 765)

Mean of the point positions for the point 12 is as follows [{1/13*(809+893+855+878+922+832+868+815+912+884+879+913+898),{1/13*(868+862+879+889+994+869+929+931+920+869+948+880+787)}]=(873,894)

Mean of the point positions for the point 13 is as follows [{1/13*(891+987+938+966+1014+920+956+914+994+977+979+1000+982),{1/13*(839+829+847+846+958+829+894+900+885+841+932+837+753)}]=(962,860)

Mean of the point positions for the point 14 is as follows [{1/13*(972+1085+1031+1059+1107+998+1060+1000+1074+1068+1070+1088+1066),{1/13*(869+853+881+880+990+874+929+925+915+869+950+867+789)}]=(1052,891)

Mean of the point positions for the point 15 is as follows [{1/13*(891+987+939+971+1015+917+956+908+992+976+977+1007+979),{1/13*(888+875+927+906+1023+898+952+ 969+946+897+983+910+823)}] = (962, 922)

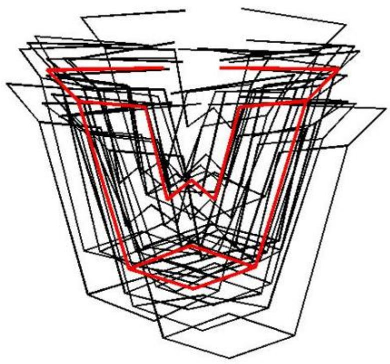

Figure 7. Mean Face In Red Colour

5. Conclusion & Future Work

Automatic Landmark point localization and after that storing those coordinate values is a challenging task to generate the example shapes in ASM. In this paper, we describe a manual approach to localize landmark points for example shape generation. This approach uses a simpler shape which can be used for human face alignment. It uses less number of points to generate the example shapes. This example shapes (fig 4) of human faces are simpler than that of other methods. In future work of our study we will use the mean face “Fig 7” and we will apply PCA for the image alignment. As a result we can easily recognize any human being using this example shapes.

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